



University of Pennsylvania
ScholarlyCommons

Departmental Papers (CIS)

Department of Computer & Information Science

9-2010

Using Entity Features to Classify Implicit Discourse Relations

Annie Louis

University of Pennsylvania

Aravind K. Joshi

University of Pennsylvania, joshi@cis.upenn.edu

Rashmi Prasad

University of Pennsylvania

Ani Nenkova

University of Pennsylvania, nenkova@cis.upenn.edu

Follow this and additional works at: http://repository.upenn.edu/cis_papers



Part of the [Computer Sciences Commons](#)

Recommended Citation

Annie Louis, Aravind K. Joshi, Rashmi Prasad, and Ani Nenkova, "Using Entity Features to Classify Implicit Discourse Relations", . September 2010.

Louis, A., Joshi, A., Prasad, R., & Nenkova, A., Using Entity Features to Classify Implicit Discourse Relations, *The 11th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, Sept. 2010, doi: [anthology/W10-4310](https://doi.org/10.1017/S1744532610000310)

This paper is posted at ScholarlyCommons. http://repository.upenn.edu/cis_papers/712

For more information, please contact libraryrepository@pobox.upenn.edu.

Using Entity Features to Classify Implicit Discourse Relations

Abstract

We report results on predicting the sense of implicit discourse relations between adjacent sentences in text. Our investigation concentrates on the association between discourse relations and properties of the referring expressions that appear in the related sentences. The properties of interest include coreference information, grammatical role, information status and syntactic form of referring expressions. Predicting the sense of implicit discourse relations based on these features is considerably better than a random baseline and several of the most discriminative features conform with linguistic intuitions. However, these features do not perform as well as lexical features traditionally used for sense prediction.

Disciplines

Computer Sciences

Comments

Louis, A., Joshi, A., Prasad, R., & Nenkova, A., Using Entity Features to Classify Implicit Discourse Relations, *The 11th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, Sept. 2010, doi: [anthology/W10-4310](#)

Using entity features to classify implicit discourse relations

Annie Louis, Aravind Joshi, Rashmi Prasad, Ani Nenkova

University of Pennsylvania

Philadelphia, PA 19104, USA

{lannie, joshi, rjprasad, nenkova}@seas.upenn.edu

Abstract

We report results on predicting the sense of implicit discourse relations between adjacent sentences in text. Our investigation concentrates on the association between discourse relations and properties of the referring expressions that appear in the related sentences. The properties of interest include coreference information, grammatical role, information status and syntactic form of referring expressions. Predicting the sense of implicit discourse relations based on these features is considerably better than a random baseline and several of the most discriminative features conform with linguistic intuitions. However, these features do not perform as well as lexical features traditionally used for sense prediction.

1 Introduction

Coherent text is described in terms of discourse relations such as “cause” and “contrast” between its constituent clauses. It is also characterized by entity coherence, where the connectedness of the text is created by virtue of the mentioned entities and the properties of referring expressions. We aim to investigate the association between discourse relations and the way in which references to entities are realized. In our work, we employ features related to entity realization to automatically identify discourse relations in text.

We focus on implicit relations that hold between adjacent sentences in the absence of discourse connectives such as “because” or “but”. Previous studies on this task have zeroed in on lexical indicators of relation sense: dependencies between words (Marcu and Echihiabi, 2001; Blair-Goldensohn et al., 2007) and the semantic orientation of words (Pitler et al., 2009), or on general syntactic regularities (Lin et al., 2009).

The role of entities has also been hypothesized as important for this task and entity-related features have been used alongside others (Corston-Oliver, 1998; Sporleder and Lascarides, 2008). Corpus studies and reading time experiments performed by Wolf and Gibson (2006) have in fact demonstrated that the type of discourse relation linking two clauses influences the resolution of pronouns in them. However, the predictive power of entity-related features has not been studied independently of other factors. Further motivation for studying this type of features comes from new corpus evidence (Prasad et al., 2008), that *about a quarter of all adjacent sentences are linked purely by entity coherence*, solely because they talk about the same entity. Entity-related features would be expected to better separate out such relations.

We present the first comprehensive study of the connection between entity features and discourse relations. We show that there are notable differences in properties of referring expressions across the different relations. Sense prediction can be done with results better than random baseline using only entity realization information. Their performance, however, is lower than a knowledge-poor approach using only the words in the sentences as features. The addition of entity features to these basic word features is also not beneficial.

2 Data

We use 590 Wall Street Journal (WSJ) articles with overlapping annotations for discourse, coreference and syntax from three corpora.

The Penn Discourse Treebank (PDTB) (Prasad et al., 2008) is the largest available resource of discourse relation annotations. In the PDTB, implicit relations are annotated between adjacent sentences in the same paragraph. They are assigned senses from a hierarchy containing four top level categories—*Comparison*, *Contingency*, *Temporal* and *Expansion*.

An example “Contingency” relation is shown below. Here, the second sentence provides the cause for the belief expressed in the first.

Ex 1. These rate indications aren’t directly comparable. Lending practices vary widely by location.

Adjacent sentences can also become related solely by talking about a common entity without any of the above discourse relation links between their propositions. Such pairs are annotated as *Entity Relations (EntRels)* in the PDTB, for example:

Ex 2. Rolls-Royce Motor Cars Inc. said it expects its U.S sales to remain steady at about 1,200 cars in 1990. The luxury auto maker last year sold 1,214 cars in the U.S.

We use the coreference annotations from the Ontonotes corpus (version 2.9) (Hovy et al., 2006) to compute our gold-standard entity features. The WSJ portion of this corpus contains 590 articles. Here, nominalizations and temporal expressions are also annotated for coreference but we use the links between noun phrases only. We expect these features computed on the gold-standard annotations to represent an upper bound on the performance of entity features.

Finally, the Penn Treebank corpus (Marcus et al., 1994) is used to obtain gold-standard parse and grammatical role information.

Only adjacent sentences within the same paragraph are used in our experiments.

3 Entity-related features

We associate *each* referring expression in a sentence with a set of attributes as described below. In Section 3.2, we detail how we combine these attributes to compute features for a sentence pair.

3.1 Referring expression attributes

Grammatical role. In exploratory analysis of Comparison relations, we often observed *parallel* syntactic realizations for entities in the subject position of the two sentences:

Ex 3. {Longer maturities}_{E1} are thought to indicate declining interest rates. {Shorter maturities}_{E2} are considered a sign of rising rates because portfolio managers can capture higher rates sooner.

So, for each noun phrase, we record whether it is the subject of a main clause (*msubj*), subject of other clauses in the sentence (*esubj*) or a noun phrase not in subject position (*other*).

Given vs. New. When an entity is first introduced in the text, it is considered a *new* entity. Subsequent mentions of the same entity are *given*

(Prince, 1992). New-given distinction could help to identify some of the Expansion and Entity relations. When a sentence elaborates on another, it might contain a greater number of new entities.

We use the Ontonotes coreference annotations to mark the information status for entities. For an entity, if an antecedent is found in the previous sentences, it is marked as *given*, otherwise it is a *new* entity.

Syntactic realization. In Entity relations, the second sentence provides more information about a specific entity in the first and a definite description for this second mention seems likely. Also, given the importance of named entities in news, entities with proper names might be the ones frequently described using Entity relations.

We use the part of speech (POS) tag associated with the head of the noun phrase to assign one of the following categories: *pronoun*, *nominal*, *name* or *expletive*. When the head does not belong to the above classes, we simply record its POS tag. We also mark whether the noun phrase is a *definite description* using the presence of the article ‘the’.

Modification. We expected modification properties to be most useful for predicting Comparison relations. Also, named or new entities in Entity relations are very likely to have post modification.

We record whether there are premodifiers or postmodifiers in a given referring expression. In the absence of pre- and postmodifiers, we indicate *bare head* realization.

Topicalization. Preposed prepositional or adverbial phrases before the subject of a sentence indicate the topic under which the sentence is framed. We observed that this property is frequent in Comparison and Temporal relations. An example Comparison is shown below.

Ex 4. {Under British rules}_{T1}, Blue Arrow was able to write off at once \$1.15 billion in goodwill arising from the purchase. {As a US-based company}_{T2}, Blue Arrow would have to amortize the good will over as many as 40 years, creating a continuing drag on reported earnings.

When the left sibling of a referring expression is a topicalized phrase, we mark the *topic* attribute.

Number. Using the POS tag of the head word, we note whether the entity is singular or plural.

3.2 Features for classification

Next, for each *sentence pair*, we associate two sets of features using the attributes described above.

Let $S1$ and $S2$ denote the two adjacent sentences in a relation, where $S1$ occurs first in the text.

Sentence level. These features characterize $S1$ and $S2$ individually. For each sentence, we add a feature for each of the attributes described above. The value of the feature is the number of times that attribute is observed in the sentence; i.e., the feature $S1given$ would have a value of 3 if there are 3 *given* entities in the first sentence.

Sentence pair. These features capture the interactions between the entities present in $S1$ and $S2$.

Firstly, for each pair of entities (a , b), such that a appears in $S1$ and b appears in $S2$, we assign one of the following classes: (i) SAME: a and b are coreferent, (ii) RELATED: their head words are identical, (iii) DIFFERENT: neither coreferent nor related. The RELATED category was introduced to capture the parallelism often present in Comparison relations. Even though the entities themselves are not coreferent, they share the same head word (i.e. *longer maturities* and *shorter maturities*).

For features, we use the combination of the class ((i), (ii) or (iii)) with the cross product of the attributes for a and b . For example if a has attributes {*msubj*, *noun*, ...} and b has attributes {*esubj*, *defdesc*, ...} and a and b are coreferent, we would increment the count for features—{*sameS1msubjS2esubj*, *sameS1msubjS2defdesc*, *sameS1nounS2esubj*, *sameS1nounS2defdesc* ...}.

Our total set of features observed for instances in the training data is about 2000.

We experimented with two variants of features: one using coreference annotations from the Ontonotes corpus (*gold-standard*) and another based on *approximate* coreference information where entities with identical head words are marked as coreferent.

4 Experimental setup

We define five classification tasks which disambiguate if a specific PDTB relation holds between adjacent sentences. In each task, we classify the relation of interest (*positive*) versus a category with a naturally occurring distribution of *all* of the other relations (*negative*).

Sentence pairs from sections 0 to 22 of WSJ are used as training data and we test on sections 23 and 24. Given the skewed distribution of positive and negative examples for each task, we randomly downsample the negative instances in the training set to be equal to the positive examples. The sizes

of training sets for the tasks are

Expansion vs other (4716)

Contingency vs other (2466)

Comparison vs other (1138)

Temporal vs other (474)

EntRel vs other (2378)

Half of these examples are positive and the other negative in each case.

The test set contains 1002 sentence pairs: Comp. (133), Cont. (230), Temp. (34), Expn. (369), EntRel (229), NoRel¹ (7). We do not downsample our test set. Instead, we evaluate our predictions on the natural distribution present in the data to get a realistic estimate of performance.

We train a linear SVM classifier (LIBLINEAR²) for each task.³ The optimum regularization parameter was chosen using cross validation on the training data.

5 Results

5.1 Feature analysis

We ranked the features (based on gold-standard coreference information) in the training sets by their *information gain*. We then checked which attributes are common among the top five features for different classification tasks.

As we had expected, the topicalization attribute and RELATED entities frequently appear among the top features for Comparison.

Features with the *name* attribute were highly predictive of Entity relations as hypothesized. However, while we had expected Entity relations to have a high rate of coreference, we found coreferent mentions to be very indicative of Temporal relations: all the top features involve the SAME attribute. A post-analysis showed that close to 70% of Temporal relations involve coreferent entities compared to around 50% for the other classes.

The number of pronouns in the second sentence was most characteristic of the Contingency relation. In the training set for Contingency task, about 45% of sentences pairs belonging to Contingency relation have a pronoun in the second sentence. This is considerably larger than 32%, which is the percentage of sentence pairs in the negative examples with a pronoun in second sentence.

¹PDTB relation for sentence pair when both entity and discourse relations are absent, very rare about 1% of our data.

²<http://www.csie.ntu.edu.tw/~cjlin/liblinear/>

³SVMs with linear kernel gave the best performance. We also experimented with SVMs with radial basis kernel, Naive Bayes and MaxEnt classifiers.

5.2 Performance on sense prediction

The classification results (fscores) are shown in Table 1. The random baseline (Base.) represents the results if we predicted positive and negative relations according to their proportion in the test set.

Entity features based on both gold-standard (EntGS) and approximate coreference (EntApp) outperform the random baseline for all the tasks. The drop in performance without gold-standard coreference information is strongly noticeable only for Expansion relations.

The best improvement from the baseline is seen for predicting Contingency and Entity relations, with around 15% absolute improvement in fscore with both EntGS and EntApp features. The improvements for Comparisons and Expansions are around 11% in the approximate case. Temporal relations benefit least from these features. These relations are rare, comprising 3% of the test set and harder to isolate from other relations. Overall, our results indicate that discourse relations and entity realization have a strong association.

5.3 Comparison with lexical features

In the context of using entity features for sense prediction, one would also like to test how these linguistically rich features compare with simpler knowledge-lean approaches used in prior work.

Specifically, we compare with *word pairs*, a simple yet powerful set of features introduced by Marcu and Echiabi (2001). These features are the cross product of words in the first sentence with those in the second.

We trained classifiers on the word pairs from the sentences in the PDTB training sets. In Table 1, we report the performance of word pairs (WP) as well as their combination with gold-standard entity features (WP+EntGS). Word pairs turn out as stronger predictors for all discourse relations compared to our entity features (except for Expansion prediction with EntGS features). Further, no benefits over word pair results are obtained by combining entity realization information.

6 Conclusion

In this work, we used a task-based approach to show that the two components of coherence—discourse relations and entities—are related and interact with each other. Coreference, givenness, syntactic form and grammatical role of entities can predict the implicit discourse relation between ad-

Task	Base.	EntGS	EntApp	WP	WP+EntGS
Comp vs Oth.	13.27	24.18	24.14	27.30	26.19
Cont vs Oth.	22.95	37.57	38.16	38.17	38.99
Temp vs Oth.	3.39	7.58	5.61	11.09	10.04
Expn vs Oth.	36.82	52.42	47.82	48.54	49.06
Ent vs Oth.	22.85	38.03	36.73	38.48	38.14

Table 1: Fscore results

jacent sentences with results better than random baseline. However, with respect to developing automatic discourse parsers, these entity features are less likely to be useful. They do not outperform or complement simpler lexical features. It would be interesting to explore whether other aspects of entity reference might be useful for this task, such as bridging anaphora. But currently, annotations and tools for these phenomena are not available.

References

- S. Blair-Goldensohn, K. McKeown, and O. Rambow. 2007. Building and refining rhetorical-semantic relation models. In *HLT-NAACL*.
- S.H. Corston-Oliver. 1998. Beyond string matching and cue phrases: Improving efficiency and coverage in discourse analysis. In *The AAAI Spring Symposium on Intelligent Text Summarization*.
- E. Hovy, M. Marcus, M. Palmer, L. Ramshaw, and R. Weischedel. 2006. Ontonotes: the 90% solution. In *NAACL-HLT*.
- Z. Lin, M. Kan, and H.T. Ng. 2009. Recognizing implicit discourse relations in the Penn Discourse Treebank. In *EMNLP*.
- D. Marcu and A. Echiabi. 2001. An unsupervised approach to recognizing discourse relations. In *ACL*.
- M. Marcus, B. Santorini, and M. Marcinkiewicz. 1994. Building a large annotated corpus of english: The penn treebank. *Computational Linguistics*.
- E. Pitler, A. Louis, and A. Nenkova. 2009. Automatic sense prediction for implicit discourse relations in text. In *ACL-IJCNLP*.
- R. Prasad, N. Dinesh, A. Lee, E. Miltsakaki, L. Robaldo, A. Joshi, and B. Webber. 2008. The penn discourse treebank 2.0. In *LREC*.
- E. Prince. 1992. The zpg letter: subject, definiteness, and information status. In *Discourse description: diverse analyses of a fund raising text*, pages 295–325. John Benjamins.
- C. Sporleder and A. Lascarides. 2008. Using automatically labelled examples to classify rhetorical relations: An assessment. *Natural Language Engineering*, 14:369–416.
- F. Wolf and E. Gibson. 2006. *Coherence in natural language: data structures and applications*. MIT Press.